

1 **Multi-Season Lead Forecast of the North Atlantic Power**
2 **Dissipation Index (PDI) and Accumulated Cyclone Energy**
3 **(ACE)**

4
5 GABRIELE VILLARINI¹ AND GABRIEL A. VECCHI²
6

7
8 ¹ IIHR-Hydroscience & Engineering, The University of Iowa, Iowa City, Iowa
9

10 ² Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric
11 Administration, Princeton, New Jersey
12

13 Manuscript submitted to
14 *Journal of Climate*
15

16
17 June 2012
18

19
20
21 *Corresponding author address:*

22 Gabriele Villarini, IIHR-Hydroscience & Engineering, The University of Iowa, Iowa
23 City, Iowa, IA 52242. E-mail: gabriele-villarini@uiowa.edu
24

ABSTRACT

By considering the intensity, duration and frequency of tropical cyclones, the Power Dissipation Index (PDI) and Accumulated Cyclone Energy (ACE) are concise metrics routinely used to assess tropical storm activity. This study focuses on the development of a hybrid statistical-dynamical seasonal forecasting system for North Atlantic PDI and ACE over the period 1982-2011. The statistical model uses only tropical Atlantic and tropical mean sea surface temperatures (SSTs) to describe the variability exhibited by the observational record, reflecting the role of both local and non-local effects on the genesis and development of tropical cyclones in the North Atlantic basin. SSTs are predicted using a ten-member ensemble of the Geophysical Fluid Dynamics Laboratory (GFDL)-CM2.1 experimental dynamical seasonal-to-interannual prediction system. To assess prediction skill, a set of retrospective predictions is initialized for each month November-February, over the years 1981-2012. The skill assessment indicates that it is possible to make skillful predictions of ACE and PDI starting from November of the previous year: skillful predictions of the seasonally integrated North Atlantic tropical cyclone activity for the coming season could be made even while the current one is still underway. Probabilistic predictions for the upcoming 2012 North Atlantic tropical cyclone season are presented.

1 **1. Introduction**

2 The seasonal forecast of North Atlantic tropical cyclone activity has been the subject
3 of intense scientific investigation (consult Camargo *et al.* (2007) for a review). The
4 capability of performing skillful forecasts has important social and economic
5 repercussions, but also represents a way of testing our understanding of the physical
6 processes responsible for the genesis, development and tracking of these events. Seasonal
7 forecasts for the North Atlantic basin date back almost three decades, starting with the
8 work by Gray (Gray 1984a, b).

9 Ever since the 1980s, different techniques have been proposed and developed to
10 forecast tropical cyclone activity. Broadly speaking, one can consider two main
11 approaches to the seasonal forecast of tropical cyclones: one in which dynamical models
12 are used directly to forecast the tropical cyclone activity (*e.g.*, Vitart 2006; Vitart *et al.*
13 2007; LaRow *et al.* 2010; Smith *et al.* 2010; Zhao *et al.* 2010; Alessandri *et al.* 2011;
14 Chen and Lin 2011), and one in which statistical models are developed to connect the
15 future state of North Atlantic hurricane activity to predictors based on the past and
16 present state of climate (*e.g.*, Elsner and Jagger 2006; Klotzbach and Gray 2009; Wang *et al.*
17 2009). As an intermediate approach in this broad classification, one can consider
18 hybrid dynamical-statistical models, in which a statistical model, built either on observed
19 relationships (*e.g.*, Kim and Webster 2010) or on the sensitivity of tropical cyclones in
20 high resolution dynamical model experiments covering a wide range of climate states
21 (*e.g.*, Vecchi *et al.* 2011; henceforth V11), is applied to the output of dynamical
22 predictions of the future state of climate.

1 Considerable effort has been placed on the seasonal forecast of the number of tropical
2 cyclones or hurricanes (*e.g.*, Vitart 2006; Vitart *et al.* 2007; Klotzbach and Gray 2009;
3 Wang *et al.* 2009; Kim and Webster 2010; LaRow *et al.* 2010; Smith *et al.* 2010; Zhao *et*
4 *al.* 2010; V11; Alessandri *et al.* 2011; Chen and Lin 2011; Vecchi *et al.* 2012). In
5 contrast, other tropical cyclone related quantities, such as the Accumulated Cyclone
6 Energy (ACE; Camargo and Sobel 2005; Bell and Chelliah 2006) and the Power
7 Dissipation Index (PDI; Emanuel 2005, 2007), have received much less attention in the
8 seasonal hurricane prediction literature. These quantities present an integrated view of the
9 tropical cyclone season, by convolving storm duration, intensity and frequency. The
10 difference between the two metrics is that the wind speed is squared when computing
11 ACE, and cubed when computing PDI. In this study, we focus on the seasonal forecast of
12 ACE and PDI because they provide information not only on the frequency, but also on
13 the intensity and duration of the storms. The seasonal forecasting system proposed in this
14 study is a statistical-dynamical hybrid system, whose statistical component is based and
15 builds on the recent model by Villarini and Vecchi (2012; henceforth VV12) (see Section
16 2.1 for an overview of the model).

17 The effort that has gone into building our understanding of seasonal forecasts of North
18 Atlantic hurricanes has led to multiple techniques showing skill beginning from April for
19 the North Atlantic tropical cyclone season peaking in August-October (*e.g.*, Elsner and
20 Jagger 2006; Vitart 2006; Vitart *et al.* 2007; Wang *et al.* 2009; LaRow *et al.* 2010; Zhao
21 *et al.* 2010; Chen and Lin 2011). However, forecasts at longer leads remain a
22 considerable challenge. For example, the group at Colorado State University led by
23 Klotzbach and Gray issued a note on 7 December 2011 stating: “We are discontinuing

1 our early December quantitative hurricane forecast for the next year and giving a more
2 qualitative discussion of the factors which will determine next year's Atlantic basin
3 hurricane activity. Our early December Atlantic basin seasonal hurricane forecasts of the
4 last 20 years have not shown real-time forecast skill even though the hindcast studies on
5 which they were based had considerable skill”
6 (<http://hurricane.atmos.colostate.edu/forecasts/2011/dec2011/dec2011.pdf>; last accessed:
7 20 June 2012). This statement seems also to reflect the point of view expressed in AMS
8 (2000), that seasonal hurricane forecasts since the middle 1980s have shown “modest
9 forecast skill” when issued in early June and that “these forecasts have diminishing skill
10 when issued several months before the beginning of the season.”

11 So, is skillful seasonal forecast of North Atlantic tropical cyclone activity with a 6-9
12 month lead-time not achievable? V11 argued, based on a suite of retrospective forecasts,
13 that it may be possible to make skillful forecasts of North Atlantic hurricane activity from
14 November of the previous year. In this manuscript, we show through a series of
15 retrospective forecasts that it is also possible to perform skillful forecast of North Atlantic
16 PDI and ACE from as early as November of the previous year. Taken together, these
17 results suggest that it would be possible to skillfully forecast the upcoming season even
18 as the current one is coming to an end.

19 The paper is organized in the following way. In Section 2 we describe the data and
20 provide an overview of the statistical framework. Section 3 presents the results of the
21 analyses, and Section 4 summarizes the main points of the study and concludes the paper.

22

2. Data and Methodology

2.1 Statistical Model and Covariates

In this study we use the seasonally integrated North Atlantic PDI and ACE values for the period 1949-2011. The time series for these two indexes are computed from the National Oceanic and Atmospheric Administrations (NOAA) HURDAT database (*e.g.*, Jarvinen *et al.* 1984; MacAdie *et al.* 2009). The HURDAT database provides the location (latitude and longitude), minimum pressure and maximum wind speed of the center of circulation for recorded tropical storms from 1851 to the present. Similar to VV12, we correct the pre-1970 wind speed values according to Landsea (1993), use wind speed values only from tropical and subtropical, non-depression (maximum winds $> 17\text{ms}^{-1}$) stages of the storms, and focus on the 1949-2011 period to limit the impact of data inhomogeneities.

Let us indicate with Y the seasonally integrated North Atlantic PDI or ACE (PDI is normalized by a factor 10^{11} and ACE by a factor 10^9). Similar to VV12, we can model Y using a gamma distribution

$$f_Y(y|\mu, \sigma) = \frac{1}{(\sigma^2 \mu)^{1/\sigma^2}} \frac{y^{-1+1/\sigma^2} \exp[-y/(\sigma^2 \mu)]}{\Gamma(1/\sigma^2)} \quad (1)$$

in which the location parameter μ is a linear function of tropical Atlantic (SST_{Atl}) and tropical mean (SST_{Trop}) sea surface temperatures (SSTs) (via a logarithmic link function):

$$\mu = \log(\beta_0 + \beta_{Atl} SST_{Atl} + \beta_{Trop} SST_{Trop}) \quad (2)$$

and σ is constant. The mean is equal to μ , while the variance to $\mu^2 \sigma^2$.

The selection of these two predictors is supported by physical considerations and results from dynamical numerical and statistical models (*e.g.*, Shen *et al.* 2000; Sobel *et*

1 *al.* 2002; Tang and Neelin 2004; Latif *et al.* 2007; Vecchi and Soden 2007; Vecchi *et al.*
 2 2008; Ramsay and Sobel 2011; Villarini *et al.* 2010, 2011, 2012; V11; VV12). The SST
 3 anomalies are computed with respect to the period 1982- 2005. The SST_{Atl} anomalies are
 4 computed over the tropical cyclone main development region (10°-25°N and 80°-20°W),
 5 while SST_{Trop} with respect to the tropical belt 30°S-30°N. We use the NOAA's extended
 6 reconstructed SST dataset (ERSSTv3b; Smith *et al.* 2008) and averaged over the period
 7 June-November as reference input dataset. As shown in Figure 1 and described in details
 8 in VV12, this parsimonious model is able to describe very well the interannual and
 9 multidecadal variability exhibited by the observational record.

11 **2.2 Seasonal Forecasts**

12 Similar to V11, we use the forecasts of June-November SST_{Atl} and SST_{Trop} obtained
 13 from the NOAA-Geophysical Fluid Dynamics Laboratory (GFDL) experimental
 14 seasonal-to-interannual (S-I) prediction system, which is built on GFDL's Coupled Model
 15 version 2.1 (Delworth *et al.* 2006) and initialized using the coupled ensemble Kalman
 16 filter scheme of Zhang *et al.* (2007). The GFDL-CM2.1 forecasts consist of a set of
 17 retrospective predictions initialized over the period November 1981-February 2012, each
 18 with a 10-member ensemble initialized from the first day of every month with an
 19 integration of 12 months.

20 The model presented in the previous subsection (gamma distribution with μ that is a
 21 function of the two predictors and constant σ) provides the structure for our seasonal
 22 forecasting system. For the retrospective forecasts, the values of the coefficients β_0 , β_{Atl} ,
 23 and β_{Trop} (equation 2), and σ , however, are not constant over the entire period, but are

1 recomputed from year to year as new information become available over the forecast
2 period 1982-2011. For instance, the seasonal forecast for the 1982 season is based on
3 SST forecasts for 1982 and the model's parameters estimated using PDI and ACE data as
4 well as ERSSTv3b SST data from 1949 to 1980. Similarly, the seasonal forecast for 1983
5 is based on SST forecasts 1983 and the model's parameters estimated using PDI, ACE,
6 and ERSSTv3b from 1949 to 1981. We repeat this for every year from 1982 to 2011. We
7 do not use, for instance, the coefficients estimated including the information for 1981 to
8 forecast the 1982 activity because the final “best track” values (including post-season
9 adjustments) for the 1981 season would not have been available in late-1981 and early-
10 1982. As a sensitivity test, we also perform retrospective forecasts training the statistical
11 model on the entire data record – although this is not a true retrospective forecast, as it
12 requires “future” information (*i.e.*, the full 1949-2011 record was not available until
13 2012).

14 Examination of the time series of the model's coefficients highlights some interesting
15 features (Figure 2). We can clearly see two main regimes, pre-1995 and post-1995, in
16 both PDI and ACE. In the pre-1995 period, the coefficient for SST_{Atl} is smaller (in
17 magnitude) than the corresponding SST_{Trop} coefficient. This points to a reduced North
18 Atlantic tropical cyclone activity over this period. After 1995, on the other hand, we
19 observe an abrupt shift, with the SST_{Atl} coefficient becoming larger (in magnitude) than
20 the corresponding SST_{Trop} , pointing to a heightened tropical cyclone activity. Not only do
21 we observe an increase in PDI and ACE magnitude as a consequence of the changes in
22 the beta coefficients, but we also have a similar abrupt change in σ , indicating an increase
23 in variability. That 1995 emerges as a change point is coincident with the abrupt change

1 in hurricane activity that occurred in 1995 (*e.g.*, Elsner *et al.* 2004; Li and Lund 2012),
2 which was connected to changes in the state of the northern Atlantic Ocean that had
3 wide-ranging impacts (*e.g.*, Knight *et al.* 2004; Sutton and Hodson 2005; Zhang and
4 Delworth 2006). Predicting these abrupt shifts in the future will be important to
5 improving our seasonal and long-lead forecast of North Atlantic tropical cyclone activity
6 (Smith *et al.* 2010; Vecchi *et al.* 2012). It appears that this abrupt shift revealed statistical
7 relationships between SST and PDI/ACE that the shorter record did not. This shift in the
8 character of the statistical model highlights the difficulties inherent in training models on
9 finite datasets: as the record lengthened, the underlying relationships between the
10 predictors and predictand were refined. At the present time, it is unclear what physical
11 mechanisms were behind this abrupt change in the statistical model parameters, but the
12 1994-1995 climate shift in the Atlantic revealed a stronger role for Atlantic SSTs in
13 controlling hurricane activity than one would have inferred from prior data. A question
14 that, unfortunately, we cannot answer at this stage is whether the fit of PDI and ACE to
15 the SST predictors has converged, or if future shifts in the climate system will result in
16 further refinement of the model.

17 For the seasonal forecasts initialized in February, March, and April, we consider an
18 additional model configuration. It may be reasonable to expect that by February the “best
19 track” PDI and ACE values from the season that has just ended would be available, and
20 one could use these values to compute the most recent set of model's coefficients.
21 Therefore, for instance, if one wanted to forecast the PDI and ACE values for 1982, one
22 could use the coefficients estimated using all the information up to 1981, instead of being
23 restricted to the 1949-1980 period. We will show that, by adding this additional piece of

1 information, the forecasting PDI and ACE from February, March, and April nominally
2 increases.

3 The approach we follow is similar to the “retroactive validation” discussed in Mason
4 and Baddour (2007) (see also Villarini and Serinaldi (2012)), and differs from the
5 common “calibration-validation approach.” In our case, the forecast method over the
6 validation period is heterogeneous, because the statistical model from which these values
7 are obtained is not fitted over a fixed period, but over a changing one. This approach,
8 however, results from using the additional information that becomes available from year
9 to year, and has been already used in other studies and disciplines (*e.g.*, Weron 2006;
10 Villarini and Serinaldi 2012).

11 The evaluation of the forecast quality is based on visual examination of the
12 probabilistic forecasts. We use the median as our best estimate and the forecast accuracy
13 is quantified using four metrics: Pearson correlation coefficient, Spearman correlation
14 coefficient, the root mean squared error (RMSE) and the mean absolute error (MAE)
15 (*e.g.*, Wilks 2006; Hyndman and Koehler 2006). The first two metrics quantify the degree
16 of agreement between observations and forecasts. The Pearson correlation coefficient
17 quantifies the degree of linear dependence between observations and forecasts. If we
18 indicate the observations with O and the forecasts with F , it is computed as the
19 covariance between O and F normalized by the product of the standard deviation of O
20 and F . The Spearman correlation coefficient can be considered the non-parametric
21 counterpart of the Pearson correlation coefficient, and is equivalent to computing the
22 Pearson correlation coefficient on the ranked observations and forecasts. Therefore,
23 Spearman correlation coefficient is less sensitive to outliers and quantifies the degree of

monotonic dependence between O and F . The use of MAE and RMSE aims at quantifying the discrepancies between observations and forecasts, with the latter penalizing more the large discrepancies (*e.g.*, Hyndman and Koehler 2006).

3. Results

We use the parsimonious statistical model discussed in the previous section to perform retrospective forecast for every year from 1982 to 2011. Figures 3 and 4 show the results for ACE and PDI for different initialization months (description of the retrospective forecast skill for the two SST predictors is presented in V11). The models we have developed are able to describe the interannual variability exhibited by the data as early as November, indicating that it is possible to make skillful forecasts of North Atlantic PDI and ACE as early as November of the previous year. The November forecast (7-month lead time for a tropical cyclone season starting in July) is able to capture the observed alternation of quieter and more active periods. As the lead-time decreases, the median tends to follow more closely the observations, and the forecast distribution tends to better describe the data. The agreement between median forecasts and observations tends to increase going from November to January-February, likely due to an improvement in the SST forecast (V11). On the other hand, the March and April forecasts tend to be worse than the previous ones, with decreased inter-annual variability and a poorer agreement between median forecast and observations. These statements are valid for both ACE and PDI forecasts. This worsening in the seasonal forecast performance when initialized in March and April was also noted for hurricane frequency in V11. They found that the correlation between observation and forecast of tropical Atlantic SST using GFDL-

CM2.1 peaked in January and progressively decreased in February, March and April. The correlation between observed and forecasted tropical mean SST exhibited a similar pattern, with the worst agreement in the April forecasts.

Figure 5 summarizes the results regarding the accuracy of the seasonal forecast of ACE (left panels) and PDI (right panels) using the four metrics described in the previous section. Consistent with the visual assessment of Figures 3 and 4, we observe an increase in performance from November to January-February, and then a worsening in March and April. The MAE for ACE decreases from $2.8 \cdot 10^9 \text{ m}^2 \text{ s}^{-1}$ to $2.7 \cdot 10^9 \text{ m}^2 \text{ s}^{-1}$ to increase again to about $3.0 \cdot 10^9 \text{ m}^2 \text{ s}^{-1}$ in April. The MAE for PDI shows a similar pattern, with values of about $1.3 \cdot 10^{11} \text{ m}^3 \text{ s}^{-2}$ in November-December, decreasing to about $1.23 \cdot 10^{11} \text{ m}^3 \text{ s}^{-2}$ in January and February, and increasing again reaching $1.4 \cdot 10^{11} \text{ m}^3 \text{ s}^{-2}$ in April. The RMSE values are larger than the corresponding MAE values because of the increased influence of discrepancies at the extremes, and the skewed distribution of ACE and PDI. Both measures of error are smaller than the observed standard deviations of $3.8 \cdot 10^9 \text{ m}^2 \text{ s}^{-1}$ and $1.8 \cdot 10^{11} \text{ m}^3 \text{ s}^{-2}$ for ACE and PDI, respectively.

The results obtained by using the correlation coefficients indicate that this experimental seasonal forecasting system was able to reproduce well the observational record. The Pearson correlation coefficient is about 0.5 for forecasts initialized in November and December, peaking at 0.6 in January and February, and decreases down to 0.5 in March and April. The results are similar for both PDI and ACE. The results obtained by using the Spearman correlation coefficient are less dependent on the initialization month. The values for ACE are on the order of 0.55, with the exception of the January forecast, which peaks at about 0.65. The results for PDI are slightly larger,

1 with values on the order 0.58 for all the initialization months, except for January, in
2 which the correlation coefficient peaks at 0.66. The slight differences between Pearson
3 and Spearman correlation coefficients can be due to the fact that the latter works on ranks
4 rather than on the numerical values of the forecasts and observations.

5 As mentioned before, we have also examined the improvement in the forecasts
6 initialized in February to April associated with the use of the most recent PDI, ACE, and
7 SST values. Overall, the February forecasts are now more accurate than the January ones,
8 exhibiting the smallest MAE and RMSE values and the largest Pearson correlation
9 coefficients (the largest Spearman correlation coefficients are still in January). The use of
10 this additional information results in an overall improvement in the March and April
11 forecasts as well.

12 We have also used the seasonal forecasting system presented in this study to make
13 forecasts for the upcoming 2012 hurricane season (Figure 6, Table 1). Neither the
14 November nor December 2011 forecasts suggested that the 2012 season will be
15 particularly active. According to the ACE forecast, there is an 11.4% probability of
16 having a season exceeding the 1980-2010 mean based on the November forecast, and a
17 slightly larger probability according to the December forecast (17.7%). The results for
18 PDI are similar, with a probability of 10.3% (16.2%) of having a season more active than
19 the 1980-2010 mean based on the November (December) forecasts. On the other hand,
20 based on the forecasts initialized in January and February, the 2012 season is forecasted
21 to be about as active as the 1980-2010 mean. The probability of having a season more
22 active than the mean 1995-2010 period is smaller than for the 1980-2010 period, but still
23 increasingly larger going from the November to the February forecasts (Table 1). The

1 increase in forecasted activity with reduced lead-time is due to the forecast of SST, with
2 forecasts for the Atlantic Ocean warming to lag that of the rest of the tropics by less.
3 Based on the results in Figure 5, the retrospective 1982-2011 January and February
4 forecasts were generally more accurate than the November-December ones – but the
5 differences are not statistically significant. It will be interesting to check at the end of the
6 2012 season how well this forecast system will have performed.

7

8 **4. Conclusions**

9 In this study, we have proposed and developed a hybrid statistical-dynamical
10 forecasting system of North Atlantic tropical cyclone activity, targeting the seasonally
11 integrated PDI and ACE values. Predictions of these two indices complement forecasts of
12 the number of storms by also providing information on intensity and duration. Our
13 system builds on VV12 and describes the PDI and ACE time series with a gamma
14 distribution, in which the logarithm of the location parameter depends linearly on tropical
15 Atlantic and tropical mean SSTs, while the scale parameter is constant. We use the
16 GFDL-CM2.1 experimental seasonal-to-interannual forecast system (Delworth *et al.*
17 2006; Zhang *et al.* 2007; V11) to obtain the input predictors as early as November of the
18 year prior to the season we want to forecast. We used four different metrics (RMSE,
19 MAE, Pearson and Spearman correlation coefficients) to assess the forecast accuracy.

20 By performing retroactive validation (Mason and Baddour 2007), we showed that it is
21 possible to make skillful forecasts of PDI and ACE starting from November of the
22 previous year. This means that there is potential for skillful forecasts of the seasonally

1 integrated North Atlantic tropical cyclone activity for the coming season while the
2 current one is still underway.

3 Using this system, we have provided ACE and PDI forecasts for the 2012 season.
4 Based on our results, the 2012 tropical cyclone season is not forecasted to be particularly
5 active, even though the January and February 2012 forecasts indicate that it will be less
6 inactive than what the November-December 2011 forecasts suggested.

7 There are several different possible venues to improve upon this system. In this study,
8 we focused on the SST forecasts from the GFDL-CM2.1. In the future, however, it would
9 be possible to include SST forecasts from research centers around the world that already
10 routinely perform SST forecasts. Based on the results of V11, it is likely that a multi-
11 model ensemble approach would lead to an increase in the long-lead skill. Another venue
12 for future research is the application of this statistical model to decadal projections of
13 North Atlantic tropical cyclone activity. Smith *et al.* (2010) and Vecchi *et al.* (2012)
14 showed that there is potential skill in multi-year predictions of hurricane frequency.
15 Experiments are underway to assess the feasibility of multi-year to decadal forecasts of
16 PDI and ACE using the GFDL CM2.1 experimental decadal forecast system (Rosati *et al.*
17 2012; Yang *et al.* 2012; Vecchi *et al.* 2012) and the suite of Fifth Coupled Model
18 Intercomparison Project (CMIP5) initialized decadal forecast experiments (Taylor *et al.*
19 2012). The results of this study, together with those in Smith *et al.* (2010) and Vecchi *et*
20 *al.* (2012) indicate that there is hope in achieving skillful multi-year predictions of ACE
21 and PDI by considering both radiatively-forced and internal components of multi-year
22 hurricane activity changes.

23
24

1 *Acknowledgments.* Gabriele Villarini acknowledges financial support from the Iowa
2 Flood Center, IIHR-Hydroscience & Engineering.
3

REFERENCES

- Alessandri, A., A. Borrelli, S. Gualdi, E. Scoccimarro, and S. Masina, Tropical cyclone count forecasting using a dynamical seasonal prediction system: Sensitivity to improved ocean initialization, *Journal of Climate*, 24, 2963-2982, 2011.
- AMS, Policy statement: Hurricane research and forecasting, *Bulletin of the American Meteorological Society*, 6, 1341-1346, 2000.
- Bell, G. D., and M. Chelliah, Leading tropical modes associated with interannual and multidecadal fluctuations in North Atlantic hurricane activity, *Journal of Climate*, 19, 590-612, 2006.
- Camargo, S. J., and A. H. Sobel, Western North Pacific tropical cyclone intensity and ENSO, *Journal of Climate*, 18, 2996-3006, 2005.
- Camargo, S. J., A. G. Barnston, P. Klotzbach, and C. W. Landsea, *Seasonal tropical cyclone forecasts*, World Meteorological Organization Bulletin, 56, 297-309, 2007.
- Chen, J. H., and S. J. Lin, The remarkable predictability of inter-annual variability of Atlantic hurricanes during the past decade, *Geophysical Research Letters*, 38 (L11804), doi:10.1029/2011GL047629, 2011.
- Delworth, T. L., and Coauthors, GFDL's CM2 global coupled climate models. Part I: Formulation and simulation characteristics, *Journal of Climate*, 19, 643-674, 2006.
- Elsner, J. B., and T. H. Jagger, Prediction models for annual U.S. hurricane counts, *Journal of Climate*, 19, 2935-2952, 2006.

1 Elsner, J. B., X. Niu, and T. H. Jagger, Detecting shifts in hurricane rates using a Markov
2 Chain Monte Carlo approach, *Journal of Climate*, 17, 2652-2827, 2004.

3 Emanuel, K., Increasing destructiveness of tropical cyclones over the past 30 years,
4 *Nature*, 436, 686-688, 2005.

5 Emanuel, K., Environmental factors affecting tropical cyclone power dissipation, *Journal*
6 *of Climate*, 20, 5497-5509, 2007.

7 Gray, W. M., Atlantic seasonal hurricane frequency. Part I: El Niño and 30 mb quasi-
8 biennial oscillation influences, *Monthly Weather Review*, 112, 1649-1668, 1984a.

9 Gray, W. M., Atlantic seasonal hurricane frequency. Part II: Forecasting its variability,
10 *Monthly Weather Review*, 112, 1669-1683, 1984b.

11 Hyndman, R. J., and A. B. Koehler, Another look at measures of forecast accuracy,
12 *International Journal of Forecasting*, 22 (4), 679-688, 2006.

13 Jarvinen, B. R., C. J. Neumann, and M. A. S. Davis, *A tropical cyclone data tape for the*
14 *North Atlantic Basin, 1886-1983: Contents, limitations, and uses*, Technical
15 Memo NWS NHC 22, National Oceanic and Atmospheric Administration, 1984.

16 Kim, H.-M., and P. J. Webster, Extended-range seasonal hurricane forecasts for the North
17 Atlantic with a hybrid dynamical-statistical model, *Geophys. Res. Lett.*, **37**,
18 L21705, doi:10.1029/2010GL044792, 2010.

19 Klotzbach, P. J., and W. M. Gray, Twenty-five years of Atlantic basin seasonal hurricane
20 forecasts, *Geophysical Research Letters*, 36 (L09711),
21 doi:10.1029/2009GL037580, 2009.

1 Knight, J. R., R. J. Allan, C. K. Folland, M. Vellinga, and M. E. Mann, 2005: A signature
2 of persistent natural thermohaline circulation cycles in observed climate.
3 *Geophys. Res. Lett.*, **32**, L20708, doi:10.1029/2005GL024233.

4 Landsea, C. W., A climatology of intense (or major) Atlantic hurricanes, *Monthly*
5 *Weather Review*, 121, 1703-1713, 1993.

6 LaRow, T. E., L. Stefanova, D. W. Shin, and S. Cocke, Seasonal Atlantic tropical
7 cyclone hindcasting/forecasting using two sea surface temperature datasets,
8 *Geophysical Research Letters*, 37, 1-5, doi:10.1029/2009GL041459, 2010.

9 Latif, M., N. Keenlyside, and J. Bader, Tropical sea surface temperature, vertical wind
10 shear, and hurricane development, *Geophysical Research Letters*, 34 (L01710),
11 doi:10.1029/2006GL027969, 2007.

12 Li, S., and R. Lund, Multiple changepoint detection via genetic algorithms, *Journal of*
13 *Climate*, 25, 674-686, 2012.

14 MacAdie, C. J., C. W. Landsea, C. J. Neumann, J. E. David, E. Blake, and G. R.
15 Hammer, *Tropical cyclones of the North Atlantic Ocean, 1851-2006*, Technical
16 Memo, National Climatic Data Center in cooperation with the TCP/National
17 Hurricane Center, 2009.

18 Mason, S. J., and O. Baddour, Statistical modelling, in *Seasonal Climate: Forecasting*
19 *and Managing Risk*, edited by A. Troccoli, M. Harrison, D. L. T. Andersen, and
20 S. J. Mason, pp. 163-201, Springer, 2007.

21 Ramsay, H. A., and A. H. Sobel, Effects of relative and absolute sea surface temperature
22 on tropical cyclone potential intensity using a single-column model, *Journal of*
23 *Climate*, 24, 183-193, 2011.

1 Rosati, A., and co-authors, Decadal Predictions Experiments at GFDL. *J. Climate* (in
2 preparation), 2012.

3 Shen, W., R. E. Tuleya, and I. Ginis, A sensitivity study of the thermodynamic
4 environment on GFDL model hurricane intensity: Implications for global
5 warming, *Journal of Climate*, 13, 109-121, 2000.

6 Smith, D. M., R. Eade, N. J. Dunstone, D. Fereday, J. M. Murphy, H. Pohlmann, and A.
7 A. Scaife, Skillful multi-year predictions of Atlantic hurricane frequency, *Nature*
8 *Geoscience*, 3, 846-849, 2010.

9 Smith, T. M., R. W. Reynolds, T. C. Peterson, and J. Lawrimore, Improvement to
10 NOAA's historical merged land-ocean surface temperature analysis (1880-2006),
11 *Journal of Climate*, 21, 2283-2296, 2008.

12 Sobel, A. H., I. M. Held, and C. S. Bretherton, The ENSO signal in tropical tropospheric
13 temperature, *Journal of Climate*, 15, 2702-2706, 2002.

14 Sutton, R. T. and D. L. R. Hodson, Atlantic Ocean forcing of North American and
15 European summer climate, *Science*, **309**(5731), 115-118, 2005.

16 Tang, B. H., and J. D. Neelin, ENSO influence on Atlantic hurricanes via tropospheric
17 warming, *Geophysical Research Letters*, 31 (L24204),
18 doi:10.1029/2004GL021072, 2004.

19 Taylor, K. E., R. J. Stouffer, and G. A. Meehl, An overview of CMIP5 and the
20 experiment design, *Bulletin of the American Meteorological Society*, **93**, 485-498,
21 2012.

22 Vecchi, G. A., and B. J. Soden, Effect of remote sea surface temperature change on
23 tropical cyclone potential intensity, *Nature*, 450, 1066-1071, 2007.

1 Vecchi, G. A., K. L. Swanson, and B. J. Soden, Whither hurricane activity?, *Science*,
2 322, 687-689, 2008.

3 Vecchi, G. A., M. Zhao, H. Wang, G. Villarini, A. Rosati, A. Kumar, I. M. Held, and R.
4 Gudgel, Statistical-dynamical predictions of seasonal North Atlantic hurricane
5 activity, *Monthly Weather Review*, 139 (4), 1070-1082, 2011.

6 Vecchi, G. A., R. Msadek, W. Anderson, Y. C. Chang, T. Delworth, K. Dixon, R.
7 Gudgel, A. Rosati, B. Stern, , G. Villarini, A. Wittenberg, X. Yiang, R. Zhang, S.
8 Zhang, and F. Zeng, Multi-year predictions of North Atlantic hurricane
9 frequency: Promise and limitations, *Journal of Climate*, 2012 (in preparation).

10 Villarini, G., and F. Serinaldi, Development of statistical models for at-site probabilistic
11 seasonal rainfall forecast, *International Journal of Climatology*,
12 doi:10.1002/joc.3393, in press, 2012.

13 Villarini, G., and G. A. Vecchi, North Atlantic Power Dissipation Index (PDI) and
14 Accumulated Cyclone Energy (ACE): Statistical modeling and sensitivity to sea
15 surface temperature changes, *Journal of Climate*, 25 (2), 625-637, 2012.

16 Villarini, G., G. A. Vecchi, and J. A. Smith, Modeling of the dependence of tropical
17 storm counts in the North Atlantic Basin on climate indices, *Monthly Weather*
18 *Review*, 138 (7), 2681-2705, 2010.

19 Villarini, G., G. A. Vecchi, T. R. Knutson, M. Zhao, and J. A. Smith, North Atlantic
20 tropical storm frequency response to anthropogenic forcing: Projections and
21 sources of uncertainty, *Journal of Climate*, 24 (13), 3224-3238, 2011.

- 1 Villarini, G., G. A. Vecchi, and J. A. Smith, U.S. landfalling and North Atlantic
2 hurricanes: Statistical modeling of their frequencies and ratios, *Monthly Weather*
3 *Review*, 140 (1), 44-65, 2012.
- 4 Vitart, F., Seasonal forecasting of tropical storm frequency using a multi-model
5 ensemble, *Quarterly Journal of the Royal Meteorological Society*, 132, 647-666,
6 2006.
- 7 Vitart, F., M. Huddleston, D. Deque, T. Palmer, T. Stockdale, M. Davey, S. Ineson, and
8 A. Weisheimer, Dynamically-based seasonal forecasts of Atlantic tropical storm
9 activity issued in June by EUROSIP, *Geophysical Research Letters*, 34 (L16815),
10 doi:10.1029/2007GL030740, 2007.
- 11 Wang, H., J. K. E. Schemm, A. Kumar, W. Wang, L. Long, M. Chelliah, G. D. Bell, and
12 P. Peng, A statistical forecast model for Atlantic seasonal hurricane activity based
13 on the NCEP dynamical seasonal forecast, *Journal of Climate*, 22, 4481-4500,
14 2009.
- 15 Weron, R., *Modeling and Forecasting Electricity Loads and Prices: A Statistical*
16 *Approach*, Wiley, Chichester, 2006.
- 17 Wilks, D. S., *Statistical Methods in the Atmospheric Sciences*, 627 pp., Elsevier, 2006.
- 18 Yang, X. and co-authors, A predictable AMO-like pattern in GFDL's fully-coupled
19 ensemble initialization and decadal forecasting system. *J. Climate* (submitted),
20 2012.
- 21 Zhang, R. and T. L. Delworth, 2006: Impact of Atlantic multidecadal oscillations on
22 India/Sahel rainfall and Atlantic hurricanes. *Geophys. Res. Lett.*, **33**, L17712,
23 doi:10.1029/2006GL026267.

- 1 Zhang, S., M. J. Harrison, A. Rosati, and A. T. Wittenberg, 2007: System design and
2 evaluation of coupled ensemble data assimilation for global oceanic climate
3 studies. *Mon. Wea. Rev.*, **135**, 3541–3564.
- 4 Zhao, M., I. M. Held, and G. A. Vecchi, Retrospective forecasts of the hurricane season
5 using a global atmospheric model assuming persistence of SST anomalies,
6 *Monthly Weather Review*, 138, 3858-3868, 2010.
- 7

1

LIST OF TABLES

2

3 TABLE 1. Summary of the probabilities of having a 2012 season as active as or more

4 active than the 1980-2010 and 1995-2010 means.

5

6

LIST OF FIGURES

FIG. 1. Results of the statistical modeling of ACE (top panel) and PDI (bottom panel) over the period 1949-2011. These results are based on fitting the observational record (corrected according to Landsea (1993); black circles) using a gamma distribution in which the location parameter μ is a linear function of SST_{Atl} and SST_{Trop} (via a logarithmic link function) and constant scale parameter σ . The SST data are based on ERSSTv3b data. The white line represents the median (50th percentile); the light grey area represents the region between the 5th and 95th percentiles, while the dark grey area the region between the 25th and 75th percentiles.

FIG. 2. Time series of the model coefficients for the location parameter μ (equation 2) and scale parameter σ over the period 1980-2011 for ACE (black line) and PDI (grey line).

FIG. 3. Seasonal forecast of ACE initialized from November of the year prior to the one to forecast to April (same year as the one to forecast). The black circles represent the observations. The white line represents the median (50th percentile); the light grey area represents the region between the 5th and 95th percentiles, while the dark grey area the region between the 25th and 75th percentiles. The hatched regions represent the forecasted period.

FIG. 4. Same as Figure 3 but for the PDI.

FIG. 5. Summary of the accuracy of the seasonal forecast of ACE (left panels) and PDI (right panels) for different initialization months. The metrics used are MAE, RMSE, Person and Spearman correlation coefficients. The grey horizontal line (“Most complete mode”) represents the results obtained by using the median from Figure 1 as reference

1 value. The black lines and grey circles represent the results using the medians from
2 Figures 3 and 4. The black lines and squares represent the results for the model
3 configuration using the coefficients of the statistical model estimated using all the
4 information available for that year, and the SST forecast for the upcoming year.

5
6 FIG. 6. Seasonal forecast of ACE (top panel) and PDI (bottom panel) initialized in
7 November and December 2011, and January and February 2012. The limits of the boxes
8 represent the 25th and 75th percentiles, while the whiskers the 10th and 90th percentiles.
9 The line and the square within the box represent the median and mean values,
10 respectively. The ACE and PDI values averaged over the periods 1980-2010 (solid grey
11 line) and 1995-2010 (dashed grey line) are included as reference.

1 TABLE 1. Summary of the probabilities of having a 2012 season more active than the
2 1980-2010 and 1995-2010 means for PDI and ACE and different initialization months.

3

	November	December	January	February
Probability of 2012 season more active than 1980-2010 mean (ACE)	11.4%	17.7%	29.1%	44.3%
Probability of 2012 season more active than 1995-2010 mean (ACE)	4.9%	7.8%	14.0%	28.7%
Probability of 2012 season more active than 1980-2010 mean (PDI)	10.3%	16.2%	27.0%	42.3%
Probability of 2012 season more active than 1995-2010 mean (PDI)	4.7%	7.4%	13.5%	28.4%

4

5

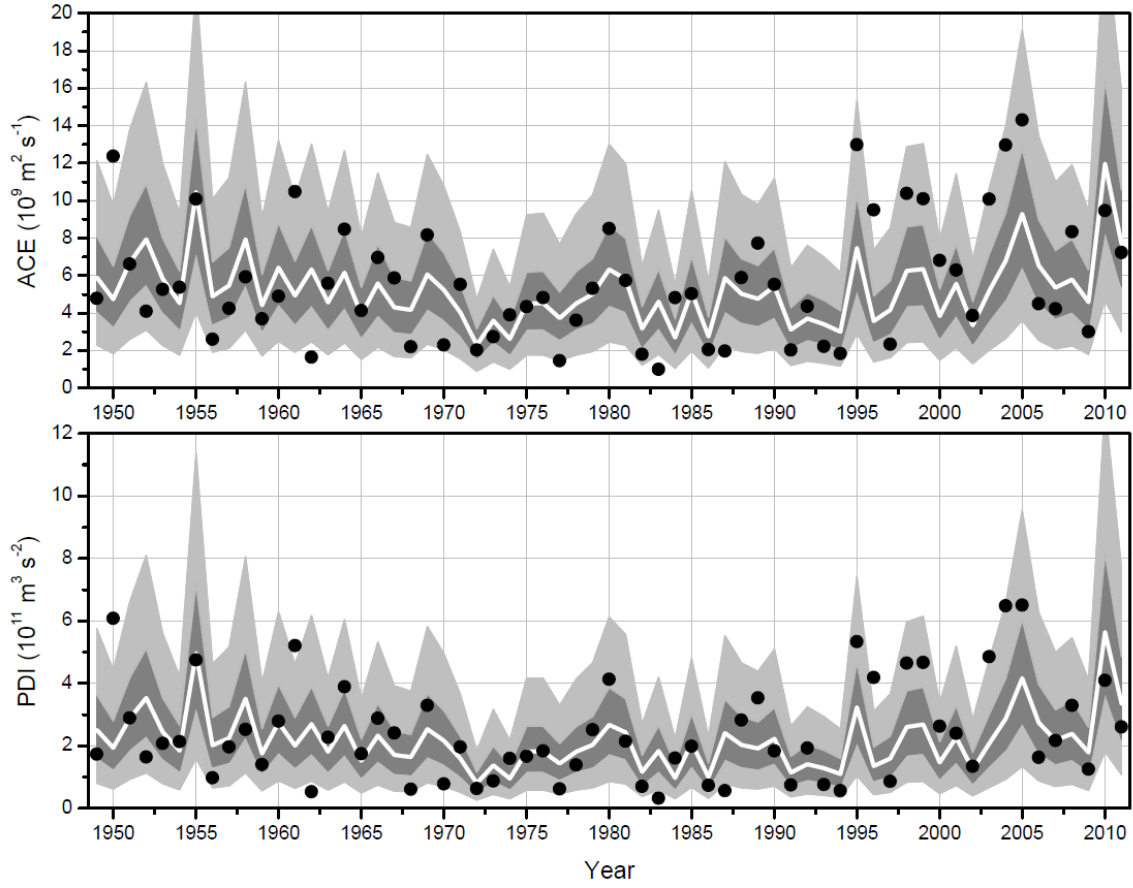


FIG. 1. Results of the statistical modeling of ACE (top panel) and PDI (bottom panel) over the period 1949-2011. These results are based on fitting the observational record (corrected according to Landsea (1993); black circles) using a gamma distribution in which the location parameter μ is a linear function of SST_{Atl} and SST_{Trop} (via a logarithmic link function) and constant scale parameter σ . The SST data are based on ERSSTv3b data. The white line represents the median (50th percentile); the light grey area represents the region between the 5th and 95th percentiles, while the dark grey area the region between the 25th and 75th percentiles.

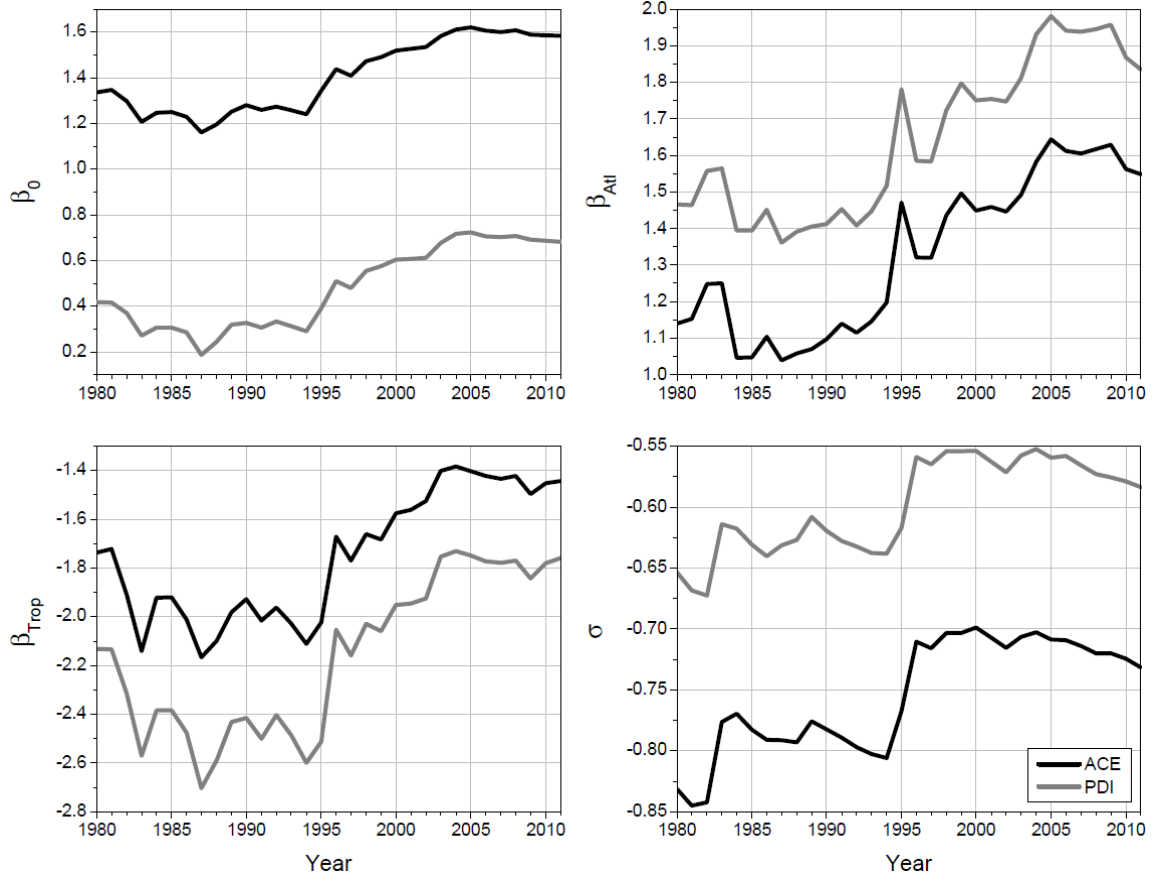
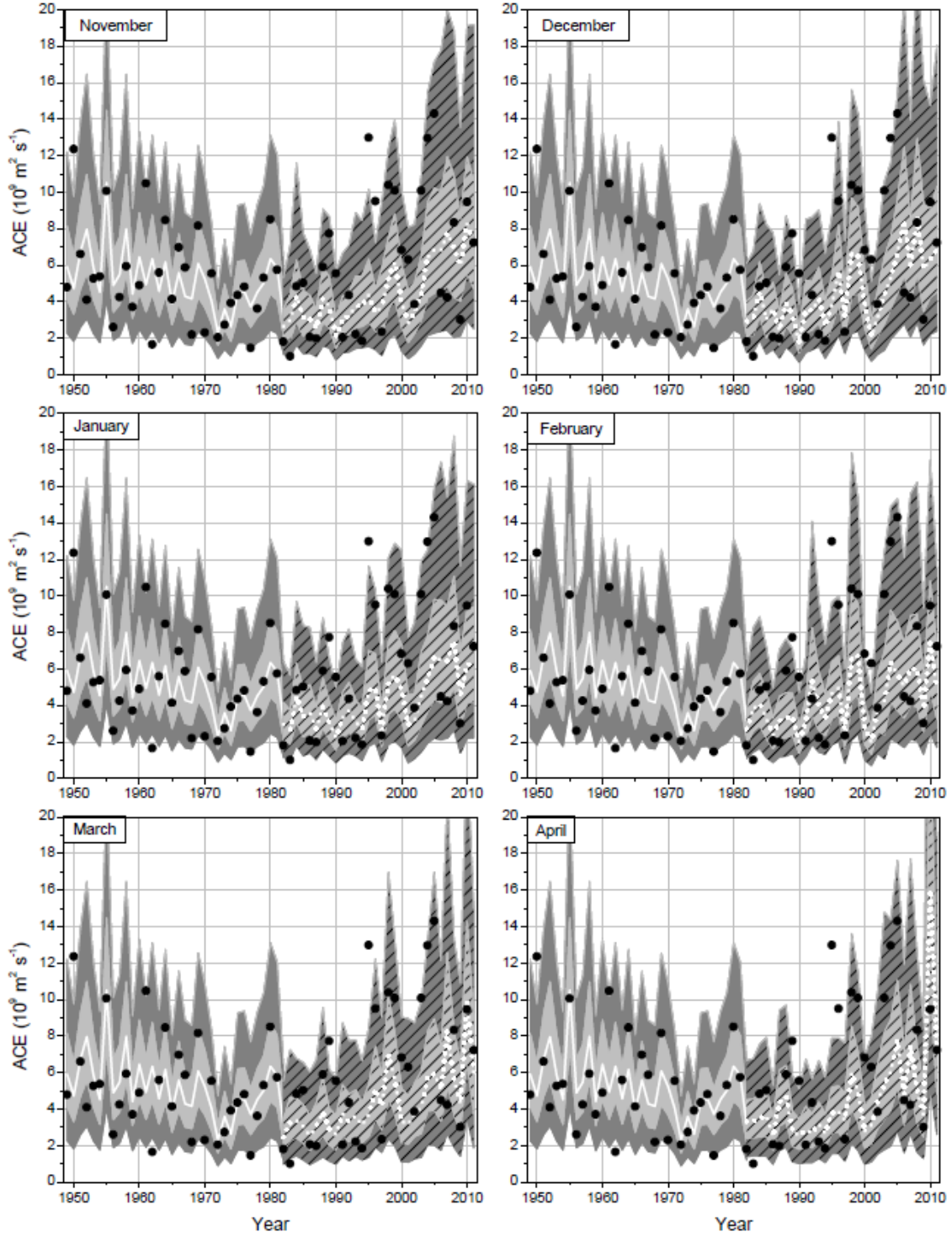


FIG. 2. Time series of the model coefficients for the location parameter μ (equation 2) and scale parameter σ over the period 1980-2011 for ACE (black line) and PDI (grey line).



1
2 FIG. 3. Seasonal forecast of ACE initialized from November of the year prior to the one
3 to forecast to April (same year as the one to forecast). The black circles represent the

1 observations. The white line represents the median (50th percentile); the light grey area
2 represents the region between the 5th and 95th percentiles, while the dark grey area the
3 region between the 25th and 75th percentiles. The hatched regions represent the forecasted
4 period.

5

6

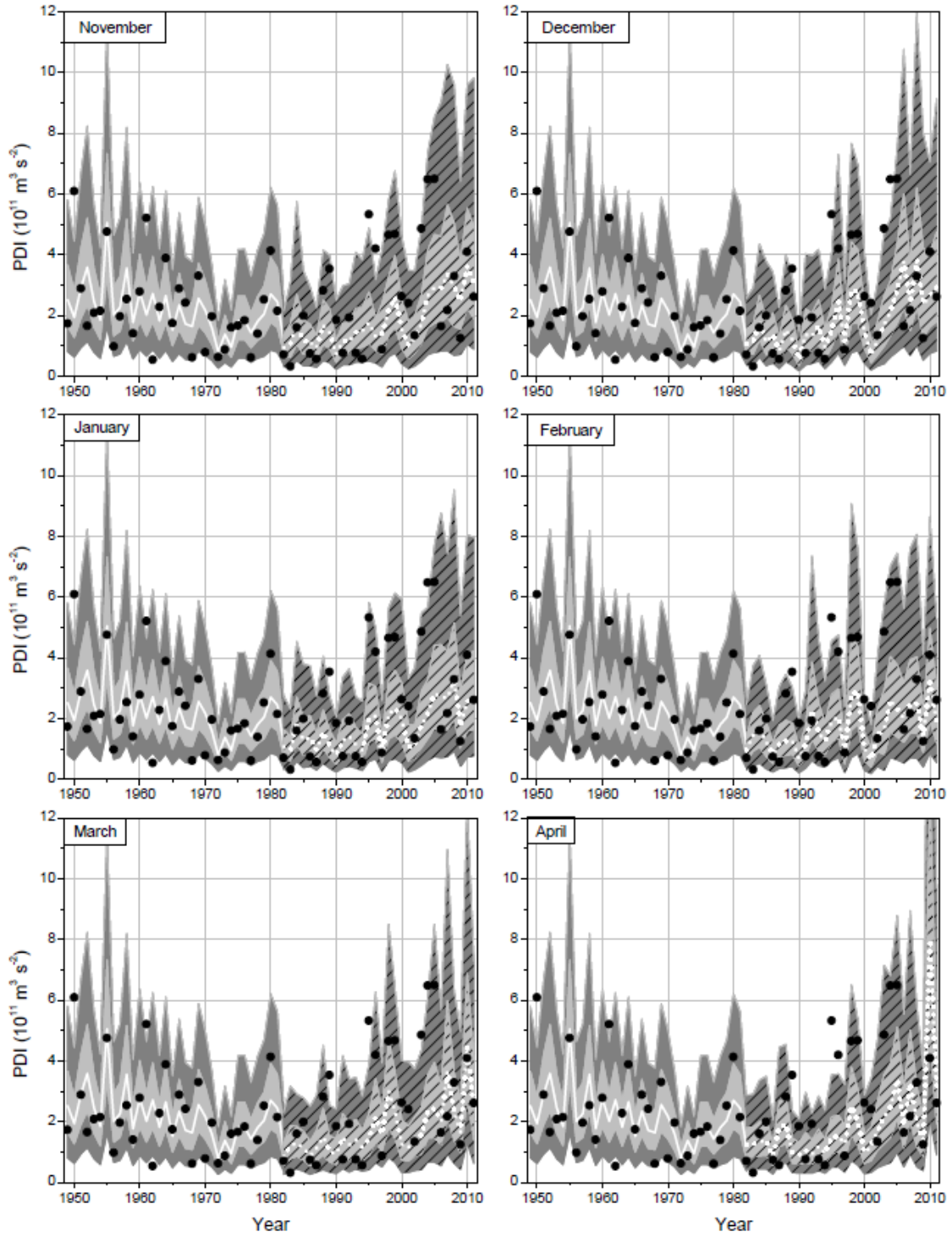
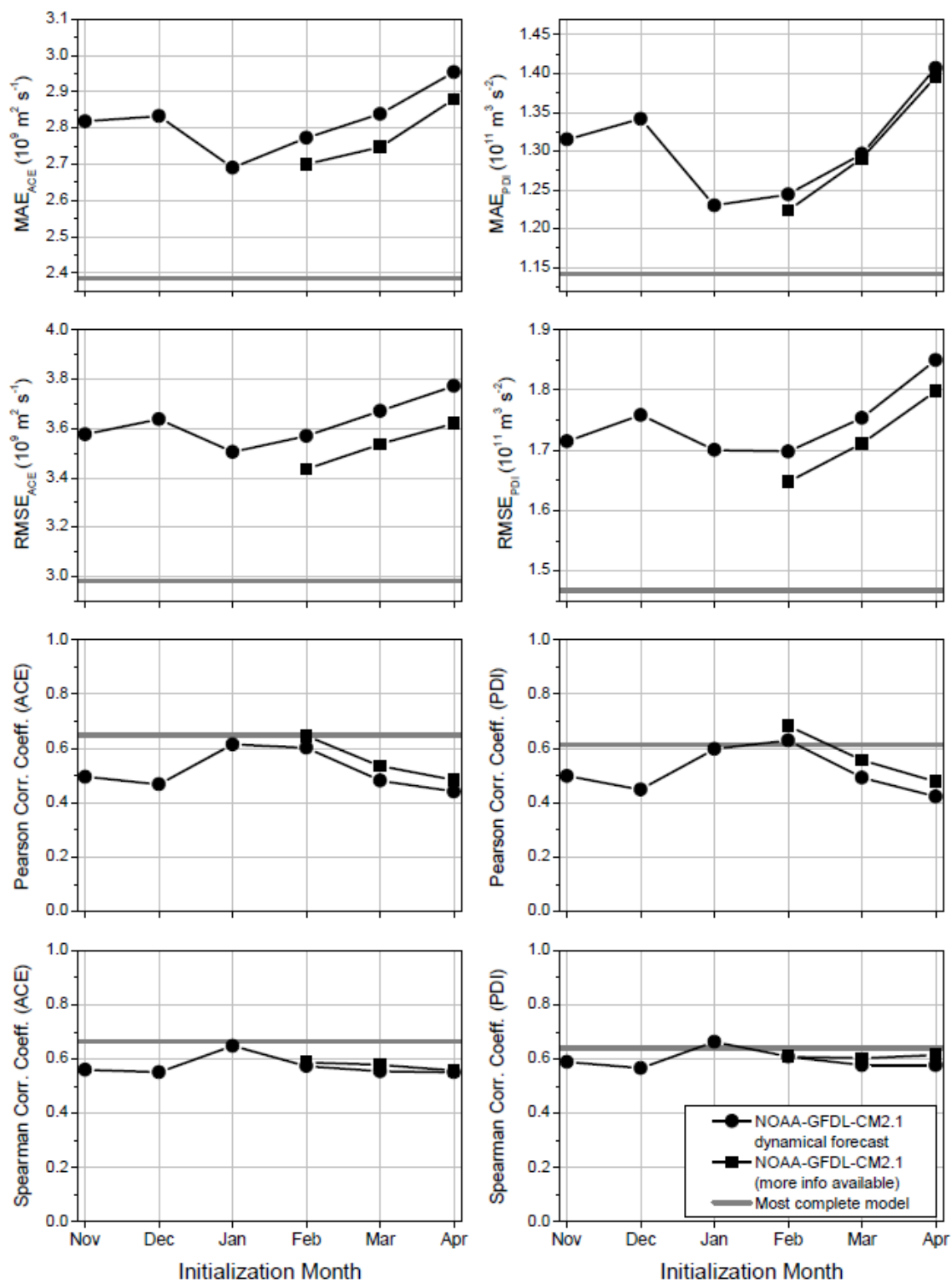


FIG. 4. Same as Figure 3 but for the PDI.

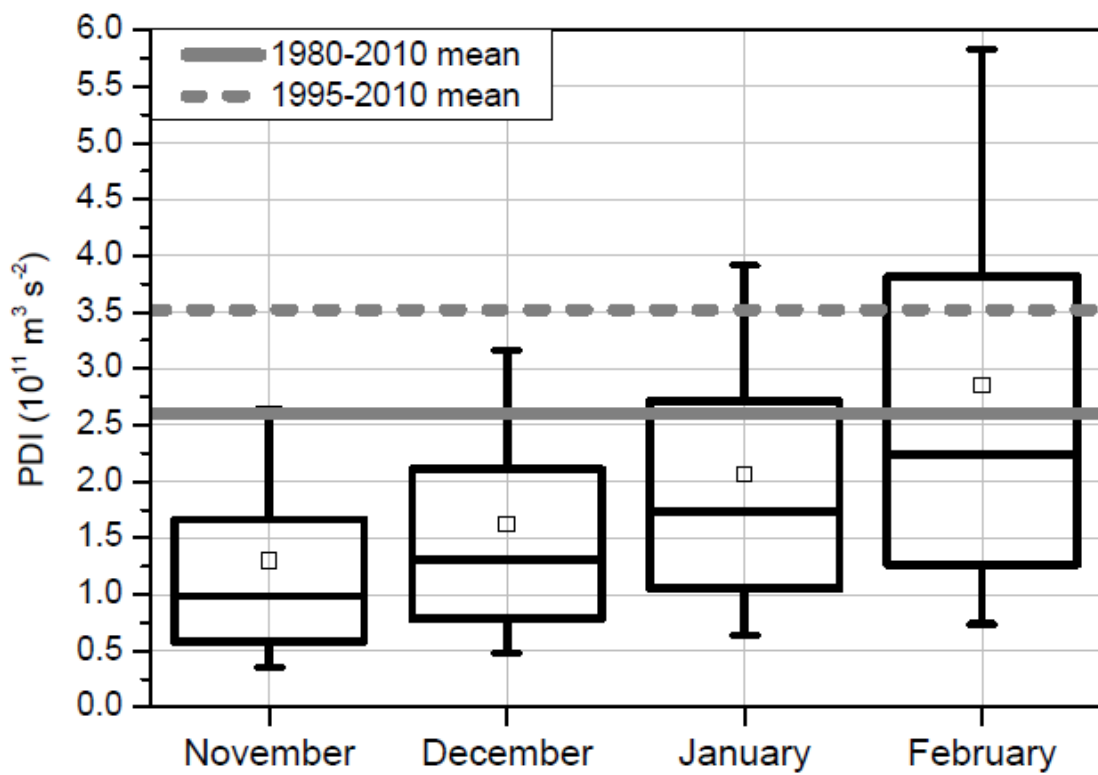
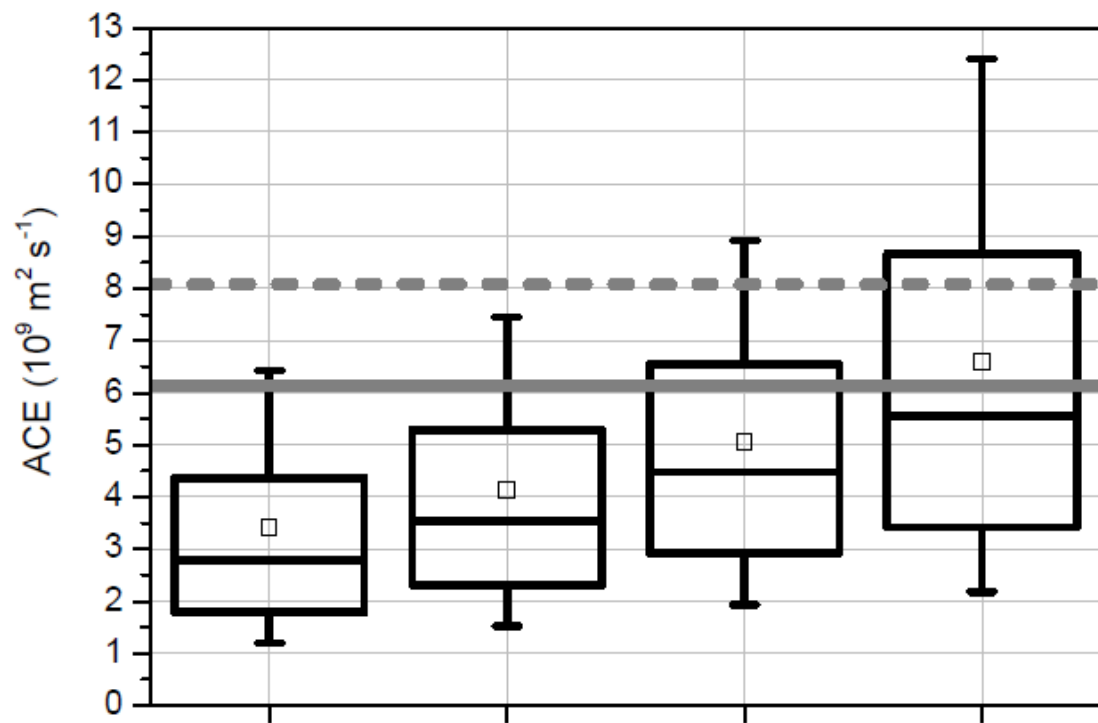


1

2

1 FIG. 5. Summary of the accuracy of the seasonal forecast of ACE (left panels) and PDI
2 (right panels) for different initialization months. The metrics used are MAE, RMSE,
3 Person and Spearman correlation coefficients. The grey horizontal line (“Most complete
4 mode”) represents the results obtained by using the median from Figure 1 as reference
5 value. The black lines and grey circles represent the results using the medians from
6 Figures 3 and 4. The black lines and squares represent the results for the model
7 configuration using the coefficients of the statistical model estimated using all the
8 information available for that year, and the SST forecast for the upcoming year.

9
10



1

2

1 FIG. 6. Seasonal forecast of ACE (top panel) and PDI (bottom panel) initialized in
2 November and December 2011, and January and February 2012. The limits of the boxes
3 represent the 25th and 75th percentiles, while the whiskers the 10th and 90th percentiles.
4 The line and the square within the box represent the median and mean values,
5 respectively. The ACE and PDI values averaged over the periods 1980-2010 (solid grey
6 line) and 1995-2010 (dashed grey line) are included as reference.